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Automatic Breast Thermography Segmentation Based on Fully Convolutional Neural Networks

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ABSTRACT

Breast cancer is one of the most cancer incidence the women world-wide. Early detection of breast cancer can increase the survival rate. Breast infrared thermography is a novel technology used for detecting early-stage breast abnormalities. The manual analysis of a huge number of these images is error-prone and consuming time and effort. Furthermore, the absence of clear edges and low contrast in thermogram may cause difficulty to analyze the image. Automated analysis of thermography images using machine learning increases the accuracy of detecting breast cancer and enables use in breast cancer screening programmes. A crucial step in the automated analysis is a segmentation, which is the aim of this paper.

The recent advances in deep learning, especially convolutional neural networks (CNNs), are making them the state-of-the-art methodology for automated image analysis. This paper presents an automated segmentation technique to extract the ROI for breast infrared thermography images, based on the use of Fully Convolutional Networks (FCN).

The experimental results prove that the accuracy, sensitivity, specificity of FCN reached to 96.4%, 97.5%, and 97.8% respectively. That denotes that the proposed automatic segmentation technique is an appropriate technique for extracting the breast ROI image from breast thermograms. Adequate comparison among recently segmentation technique by using available databases is very important, here some comparisons with other techniques are made. The comparison proves the superiority of using deep FCN over conventional algorithms.

Keywords: Breast Cancer, Thermography, Region of Interest, Segmentation, Deep convolutional neural network, deep fully convolutional networks.

INTRODUCTION

Breast cancer is the most frequent cancer among women and is the leading cause of cancer death among women. Breast cancer takes the first place for diagnosis in women among all incidence cancers and takes second place in mortality among all cancer types as reported in breast cancer statistics for the year 2019. Moreover, according to the World Health Organization (WHO), 1 in 8 women will develop breast cancer in their lifetime, and the risk of developing breast cancer increases with age. [1]

There are many techniques available to detect the presence of cancer: ultrasound, thermography, magnetic resonance imaging (MRI), microwave, X-ray, etc. Mammography is known as the gold standard imaging technique for detecting breast cancer. [2] This exam needs X-ray radiation doses to identify abnormal masses in breast volume. However, this procedure has some limitation. [3] Firstly, it is uncomfortable for the patient due to the compression of the breast. Besides that, the X-ray radiation may damage the cancerous tissue. The breast density also affects the diagnosis by mammogram images. Finally, the searchers discover that mammogram is less effective for women less than 50 years old. [4]

According to these limitations of mammography, an eminent concern has been given to thermography as an effectual breast cancer screening tool. As known for a temperature above absolute zero, all bodies transmit infrared (IR) radiation. Breast thermography technique uses a thermal infrared camera to convert this IR radiation into electrical signals and displays them as a thermogram. So, the tumor tissue is highlighted and easily detected from normal tissue in a thermogram. [5] Breast thermography has some significant advantages over mammography; such as its capability to deal with dense breast tissues and efficient in all age groups. [6] Thermography is also harmless, fast method, and helps in early detection of breast cancer. [5] Finally, the ionization, high pressure, and compression of the breast are not required in thermography. [7]

The extraction of the Region of Interest (ROI segmentation) is an essential step in any computer-aided diagnosis (CADx), computer-aided detection (CADe) system after acquiring the image. In CAD systems, a completely automatic of ROI segmentation is desirable as without any user interaction. ROI segmentation of breast thermography is the extraction and separation of the breast regions from the other parts of the body.

Due to complexities and importance of this step in the CAD, the segmentation step must provide a correct decision; and must be evaluated by comparing its performance with the manually segmented images, or the named "ground truth". Despite this, the most difficult part of evaluating segmentation of medical images is to get the ground truth, because it consumes an enormous effort and time of experts (doing a manual segmentation is very time consuming).

Obtaining of a fully automatic segmentation technique is a very hard task [8] because the thermography images have an amorphous nature and unobvious limits; and difference of the distance from which the images is taken, the image height, the breast size, image background, presence of noise etc.

There are many works in breast thermographic images segmentation. In, [9] the separation method of breast parts from the overall images was manually before the process. It performs a segmentation at which each breast is divided into four quadrants by four reference points: the chin, the left side, the right side and the bottom edge of the breast. The image is parted into four different quadrants by these four points which connected to the nipple. In, [10] an automated segmentation method is introduced using active contour and level set method without re-initialization. It separated the breast regions from the breast image. This paper employed a statistically based noise removal and contrast-limited-adaptive histogram equalization to improve the signal to noise ratio and the contrast of thermograms before utilising the level set. In, [11] the segmentation of breast ROI is performed by extracting the body boundary using the Canny edge detector and removal of internal edges. Then, it used the Fuzzy c-means clustering method for segmentation of the breast part. After that, Radon projection is applied to these segmented images for the bi-spectral invariant features extraction. In, [11] a segmentation technique is proposed at which the background region is extracted by applying the Otsu's thresholding approach; then, a reconstruction technique is used. Then the inframammary fold is identified to place the breast lower limit. Then, the upper limit of the breast is positioned by determining the axilla. Based on these two limit lines, the breast part is separated finally.

In recent years, great success has been attained in the improvement of deep learning (DL) techniques. [12] Consequently, deep Convolutional Neural Networks (CNNs) have accomplished important progress in several classification tasks and mainly in the biomedical field. [13] The key advantage of the deep networks is the capability to learn suitable feature representations in an end-to-end fashion.

Therefore, the researchers were encouraged to investigate the abilities of the most contemporary CNNs (AlexNet, VGGNet, and GoogLeNet) for pixel-wise classification (i.e. semantic segmentation) to yield enhanced performance of the segmentation task. Currently, the most widespread and successful state- of-the-art DL technique for semantic segmentation is fully convolutional networks (FCNs), which were presented by Long et al. in 2015. [14] FCNs have the same advantages of CNNs that learn by themselves can be trained end-to-end and pixel to pixel, and also produce the best performance in segmentation by hand-crafted methods. [15] AlexNet [12] was the first CNN deep network employed successfully for the classification of the ImageNet dataset and won the ILSVRC-2012 competition. [16] AlexNet is the decided framework in this paper for the implementation of the segmentation task because AlexNet requires an embedded system with limited computational power, limited memory resources, and because it has the fastest forward time over others. CNN classification models discard the spatial information by employing fully connected layers. In contrast, FCNs incorporate the spatial information by convolutionalizing the fully connected layers of CNN. The principal benefit of CNN and FCN lies in their deep architecture, which allows estimating millions of parameters to permit extracting a large number of features. [17] That needs an enormous number of training data. [18] It is also the reason why deep network gets over-fitted easily on small- and medium-size data.

The aim of this work is exploring the deep FCN to extract ROIs for a diagnostic system and conducting a feasibility study on the use of an FCN-AlexNet as an end-to-end technique for fully automated segmentation for breast thermography image. Thus, it investigates the generalization ability of the FCNs for the task of ROI segmentation. It is important to keep in mind that once the network is trained it produces the segmentation of new input images even in low-cost hardware. The performance of the model is compared to other techniques.

MATERIALS

A public database with 285 breast thermography images (in greyscale) as well as its GTs (in black and white) has been used, the image is 320x240 pixels. [19] The database could be accessed in. [20] Original images of the GTs only have the contour of the ROI (in red) and the rest of the image in white. In this work, original GT images will be converted to black and white images by assigning index 0 maps to black pixels representing the background and index 1 maps to pixels representing the ROI.

METHODS

The proposed segmentation method is directly related to transfer learning and fine-tuning techniques. Transfer learning technique is the initializing the model with the extracted parameters of pre-trained CNN-AlexNet from natural images. Fine-tuning is considered a re-training process to learn more features of a specific domain and could be for a different task. So, the proposed technique is starting with the pre-trained weights classifier weights obtained in. [21] Moreover, data augmentation technique has also been introduced to overcome the deficiency of the existing breast thermography images. Data augmentation has been proven to benefit the training of DNN; either speeding up convergence or acting as a regularizer, thus avoiding over-fitting and increasing generalization capabilities. [22] Data augmentation techniques enlarge the training dataset by generates new samples by applying a series of random transformations to the already existing data. Data augmentation can increase the size of the dataset to 10 times the original one or more. The CNNs, when presented with a huge amount of digital images starts to understand in the lower layers the basic clues like straight lines, corners, things that will help the FCN-AlexNet to understand any kind of image. The weights selected were the ones of the database PASCAL VOC 2011 segmentation challenge [23] because they presented the better results. The database used to generate this weight contains natural images (planes, birds, cats, sofas and so on) not related with the medical images used on this work but they contribute a lot to the training step because the low-level visual patterns are present in any kind of image. So, the use of these weights helped a lot the training.

Experimental

The experiment is carried out based on the augmentation of breast thermography datasets. Horizontal mirror and shift (width and height) are the two augmentation approaches employed to increase the number of available data. The horizontal mirror of data augmentation is utilized because the humans' breasts manifest horizontal mirror symmetry, so it looks to be a good approach. The shift method slipped the width and height with a fraction of the total width or height of the image. This shifting is employed to provide a translation invariance for the model.

The dataset will be divided into 80% for training, 10% for validation and 10% for testing. Then, the data augmentation approach is applied to the training set.

Two approaches of data augmentation are employed. Firstly, the training set is duplicated with the horizontal mirror. Secondly; the images displaced are in nine different locations (top-left, top-centre, top-right, centre-left, centre-centre, centre-right, bottom-left, bottom-centre and bottom-right). The size of the dataset augmentation is described in Table 1. The data augmentation techniques enlarge the training set approximately 18 times.

The input is grayscale images. The output (or label) was also in image format (black and white images). FCN-AlexNet will be training using Stochastic Gradient Descent (SGD) algorithm, with global learning rates starting from 10^{-2} with a momentum of 0.9 [12] and the batch size was equal to 1. The dropout rate [12] was 33%; the number of epochs was kept at 60. The training converged in less than 40 epochs; then, the model stopped extending in terms of knowledge. All the training took around 2 hours to converge.

Table 1: The total size of images after the augmentation approaches.

	Training	Validation	Testing
	200 images (80%)	29 images (10%)	29 images (10%)
Augmentation using Horizontal mirror	400 images	29 images	29 images
Augmentation using displacement after mirroring	3600 images	29 images	29 images

RESULT and DISCUSSION

FCN-AlexNet trained on original un-augmented images from scratch with random weights (without transfer learning); thus, the network started to over-fit. Then, the training will stop by the early stopping technique. The over-fitting of the network lies on that deep FCNs requires a huge amount of input images to correctly adjust its parameters. The accuracy curve for training and validation are shown in Figure 1; the results presented by this model are about 60% of accuracy.

As an alternative option to random initialization, the transfer learning is performed and combined with fine-tuning [24] on the augmented breast thermography images. If a fine-tuning technique is adopted, the accuracy will be improved further to 96.4 % and will significantly speed up network training, which is an important factor in the success of any deep model.

The segmentation by deep FCN could be considered as a classification task to classify each pixel in the image either as

ROI or background (BG). The evaluation of the performance for the segmentation of the two classes is listed in Table 3. Sensitivity measures the accuracy of segmentation of the ROIs by the network, while specificity measures the accuracy of segmentation of the BG. Global accuracy (GA) is the percentage of pixels correctly classified in the dataset to total pixels, regardless of class.

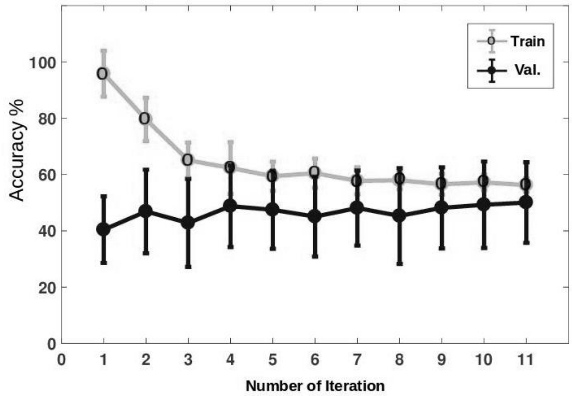

Figure 1: Training and validation accuracy curves for training from scratch.

For further evaluation, an appropriate comparison among the deep FCN-AlexNet and other techniques that used the same DMR database is established in Table. Results showed that the FCN-AlexNet had quite promising performance since none pre or pos processing was used and the input data is very small for the general idea of deep CNN. Also, The FCN-AlexNe provides promising results since no feature engineering was extracted, an automated end-to-end technique was accomplished. Figure 2 shows some samples of the input images, the segmentation result and its differences to the GT.

Table 2: Performance evaluation of FCN-AlexNet.

Model Parameter	Marques [25]	FCN-AlexNet
Accuracy	97%	96.4 %
Sensitivity	97%	97.5 %
Specificity	97%	97.8 %

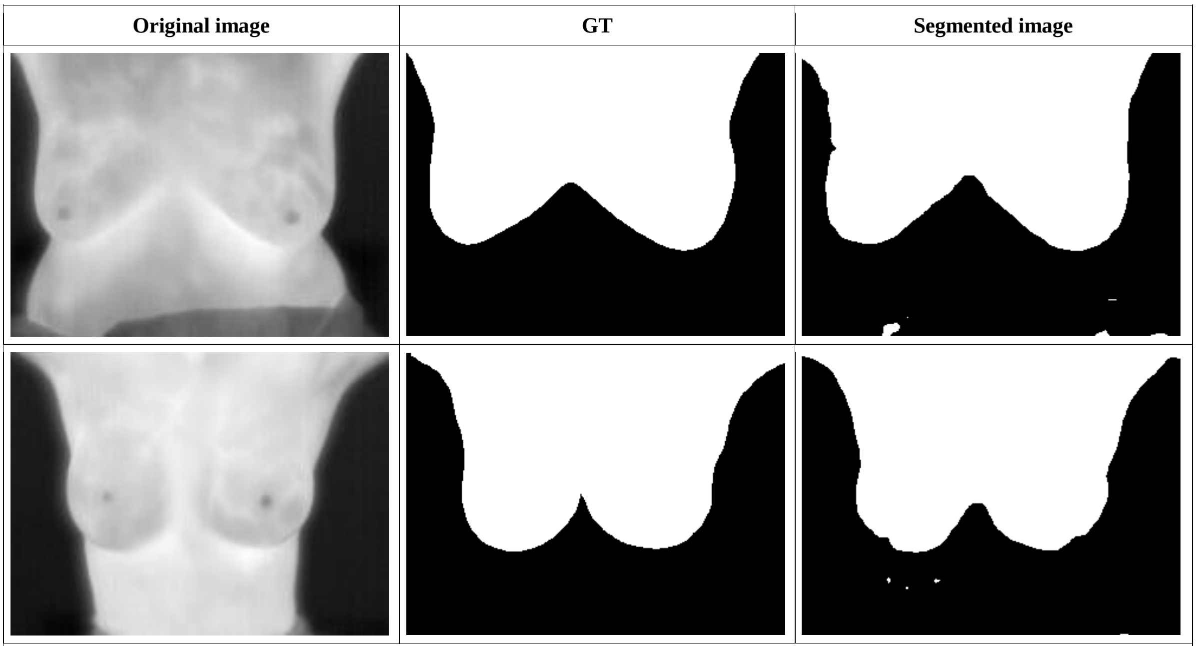

Figure 2: Samples of the segmentations.

CONCLUSION

The fully automatic segmentation model is proposed to extract the ROI of infrared breast thermography. This proposal takes advantage of an existing pre-trained deep classification network (AlexNet), by transferring its learning to the segmentation task. Since a huge amount of training data is required, the data augmentation technique is utilized to overcome data deficiency and add diversity to the dataset, which strengthen the generalization ability of the network and further alleviate over-fitting. This work is very helpful as it proves that there is no need for human interface with pre or post-processing or handcrafted features.

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